

REMOTE SENSING OF RAIN

OVER THE OCEAN

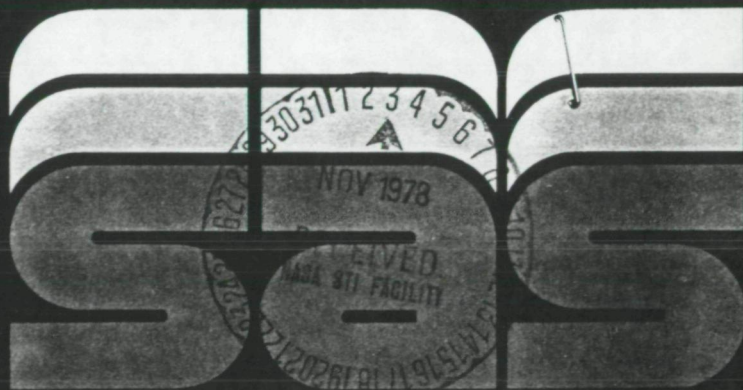
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**SYSTEMS AND APPLIED
SCIENCES CORPORATION**

6811 KENILWORTH AVENUE, SUITE 610
RIVERDALE, MARYLAND 20840

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OVER THE OCEAN

Final Report

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Prepared For:

Dr. A. T. Chang
National Aeronautics and Space Administration
Goddard Space Flight Center
Greenbelt, Maryland 20771

Prepared By:

Systems and Applied Sciences Corporation
6811 Kenilworth Avenue, Suite 610
Riverdale, Maryland 20840

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ABSTRACT

We have used computer models of the microwave emission from the earth's atmosphere to study the problem of retrieving meteorological information from the SMMR instrument that will be flown on NIMBUS-G. We describe methods of retrieving rain rate, wind speed, cloud height, and ocean temperature when the satellite is over the ocean.

FOREWORD

This report describes the work performed by Systems and Applied Sciences Corporation (SAS) under NASA Contract No. NAS5-24191. The work involved analysis of the problem of determining certain meteorological parameters from the Scanning Multichannel Microwave Radiometer (SMMR) instrument aboard NIMBUS-G, when the satellite is over the ocean. To perform this analysis, we used a computer code developed by SAS under a previous contract to generate models of the microwave emission from the earth's atmosphere. The models specifically include the effects of rain drops.

An ensemble of models was generated that simulate the microwave emission under various conditions of rain rate, ocean temperature, cloud height, and wind speed. Different methods were used to retrieve these parameters from the calculated brightness temperatures. We evaluated the accuracy of each method, and determined the limitations on our abilities to retrieve the above mentioned meteorological parameters from the SMMR data.

The balance of this report describes in detail the methods used in the retrievals and detailed estimates of the accuracy attainable with the SMMR instrument.

REMOTE SENSING OF RAIN OVER THE OCEAN

SECTION 1 - INTRODUCTION

Data from the Scanning Multichannel Microwave Radiometer (SMMR) aboard NIMBUS-G can be used, when the satellite is over the ocean, to determine wind speed, rain rate, cloud height, and ocean temperature. The experiment consists of a ten-channel radiometer that observes both vertical and horizontal polarizations at 6.6, 10.69, 18, 21, and 36.9 GHz. This report describes a theoretical investigation into the retrieval of the four above-mentioned meteorological parameters from SMMR observations. The investigation involved constructing numerical models of the microwave emission from the atmosphere above the ocean and in the presence of rain and varying the parameters of the models to generate an ensemble. The ensemble is then used to generate regression coefficients that give the value of the parameters in terms of the brightness temperatures. By doing this, we can investigate the probable limits of our ability to retrieve the desired parameters, and devise the best strategies for doing so.

We adopt, for our model, an atmosphere that is horizontally homogeneous. The lower boundary is the ocean surface. The microwave emission arises both from the atmosphere and the surface of the ocean; in addition, the ocean reflects microwaves. Because the reflection coefficients are different, in general, for the horizontal and vertical polarizations, the radiation reflected from the ocean is polarized. The effect of rain on the microwave radiance is both to increase the intensity at every wavelength and reduce the degree of polarization. The latter effect comes about because, as microwaves are scattered by the raindrops, the plane of polarization changes.

SECTION 2 - MODELS

The computer models that were generated for this investigation have four input parameters: rain rate, cloud height, surface wind speed, and ocean temperature. Other parameters that may in fact vary from place to place (or time to time) have been fixed, to make the problem tractable.

These models are used to simulate the observations under the conditions where the meteorological conditions do not vary within the field of view of the SMMR instrument. Additional models were made where only part of the field of view is covered with rain; this is discussed in Section 5.

The models have a constant vertical temperature lapse rate of 6.5 K km^{-1} , with the 273.1 K level fixed at the cloud top. The relative humidity varies linearly between 80% at the ocean surface and 100% at the cloud top. We have a layer 0.5 km thick, with its upper boundary at the cloud top, that contains non-precipitating liquid water with a density of 0.5 g m^{-3} .

The sources of opacity are molecular oxygen, water vapor, the non-precipitating liquid water, and the raindrops.

We consider the size distribution of the raindrops to be given by the Marshall-Palmer distribution

$$N(r) dr = .16 e^{-\Lambda r} dr \text{ cm}^{-3}$$

where r is the drop radius (cm), and $\Lambda = 81.56 R^{-0.21}$, where R is the nominal rain rate in mm hr^{-1} (Wilheit et al., 1976,

and references cited therein). The scattering cross-section is calculated for each drop size separately according to Mie theory and the composite scattering function is found from

$$S(\theta, \theta') = \sum N(r) p(\theta, \theta', r)$$

where $S(\theta, \theta')$ is the total cross-section for scattering from an angle θ to an angle θ' , and $p(\theta, \theta', r)$ the cross-section for a sphere of radius r .

The reflection coefficient of the ocean surface is a function of temperature, wind speed, and frequency. The reflection coefficient is calculated according to a model by Wilheit (1978). For wind speeds less than 7 m s^{-1} , the reflection coefficient is linear in wind speed; it is also linear for wind speeds greater than 7 m s^{-1} . There is a discontinuity in the slope at 7 m s^{-1} that is due to the formation of surface foam at that wind speed.

The solution of the radiative transfer equation follows the method of Herman (1963). The atmosphere is divided into a number of layers with equal optical depth, and the equation of radiative transfer is integrated in each layer for each of 12 polar angles. The solution is done by iteration; fewer than 10 iterations are required for convergence. We note that, because there is no incident radiation field at the top of the atmosphere (the 3 K cosmic background is negligible), the radiation field is azimuthally symmetric. This symmetry reduces the computing time by about an order of magnitude over what would be required in the more general case.

Two aspects of the models that are fixed are the relative humidity profile and the amount of non-precipitating liquid water below the freezing level. At each frequency, the optical depth of the atmosphere excluding the contribution of rain-drops is fixed by the choice of freezing level. For reference purposes, we have included the Appendix A table showing the total water vapor (cm) and the non-rain optical depth at each frequency.

SECTION 3 - RETRIEVAL

We generated an ensemble of 1880 models for use in the retrieval studies. In addition to the four independent parameters in the model -- rain rate, freezing level, wind speed, and ocean temperature -- it was found advantageous to add a fifth parameter, the scattering optical depth at 6.6 GHz, to the set of parameters to be retrieved. This last parameter, of course, is not independent of rain rate and freezing level.

The retrievals in this section deal only with what we call the "homogeneous" case, where the meteorological parameters are constant within the field of view. The "non-homogeneous" case is treated in Section 5, after we have discussed the general retrieval method and the accuracy of the (somewhat artificial) homogeneous retrievals in Section 4.

To do the retrieval, we represent each meteorological parameter p_i as a linear combination of functions f_i of the 10 brightness temperatures T_j . In practice, we used 3 sets of functions

$$\left. \begin{array}{ll} \text{Linear} & f_j = T_j \\ \text{Quadratic} & \begin{cases} f_j = T_j \\ f_{j+10} = T_j^2 \end{cases} \\ \text{Logarithmic} & f_j = \ln(a_j - T_j) \end{array} \right\} j = 1, 10$$

where the a_j are some constants chosen so that $a_j - T_j > 1$.

We wish to represent each parameter as

$$p_i = \sum_j \alpha_{ij} f_j$$

and determine the α_{ij} so that the residual be minimized in the least-square sense. We must consider two sources of error: one due to the difference between the fitted and the true functions, the other due to noise in the observed brightness temperatures. Let σ_j^2 be the noise in the j^{th} channel; the error in the retrieved value of p_i due to receiver noise will be

$$\begin{aligned} \sigma_{Ni}^2 &= \sum_j \sigma_j^2 \left(\frac{\partial p_i}{\partial f_j} \right)^2 \left(\frac{\partial f_j}{\partial T_j} \right)^2 \\ &= \sum_j \sigma_j^2 \alpha_{ij}^2 \end{aligned}$$

if f_j are chosen so that the average value of $\frac{\partial f_j}{\partial T_j}$ is 1.

The error in the fitting function will be

$$\chi_i^2 = \frac{1}{N} \sum_k \left(p_{ki} - \sum_j \alpha_{ij} f_{kj} \right)^2$$

and we seek to minimize the function,

$$\chi_i^2 + \sigma_{Ni}^2 = \left[\sum_j \sigma_j^2 \alpha_{ij}^2 + \frac{1}{N} \sum_k \left(p_{ki} - \sum_j \alpha_{ij} f_{kj} \right)^2 \right].$$

Here, p_{ki} is the value of the i^{th} parameter in the k^{th} model, f_{kj} the value of f_j in the k^{th} model, and N is the number of models.

We determine the covariance matrix S_{ij} by

$$S_{ij} = \frac{1}{N} \sum_k \left(f_{kj} - \bar{f}_j \right) \left(f_{ki} - \bar{f}_i \right)$$

where the superior bar represents the average over the ensemble; we define the covariance between the i^{th} parameter and f_j by

$$\sigma_{ij} = \frac{1}{N} \sum_k \left(p_{ki} - \bar{p}_i \right) \left(f_{kj} - \bar{f}_j \right).$$

We now take the derivative of $\chi_i^2 + \sigma_{Ni}^2$ within respect to each α_{ij} and set it equal to zero; this system of equations gives the values of α_{ij} that minimize $\chi_i^2 + \sigma_{Ni}^2$. The solution is

$$\alpha_{ij} = \sum_k \sigma_{ik} \hat{S}_{kj}^{-1}$$

where $\hat{S}_{kj}^{-1}$ is the inverse of the matrix

$$\hat{S}_{ij} = S_{ij} + D_{jj}$$

where D_{jj} is a diagonal matrix whose jj^{th} term is σ_j^2 .

This system can be solved either by matrix inversion or by finding the eigenvalues and eigenvectors of $\hat{S}_{ij}$, and solving for the α_{ij} in this eigenvector basis. We have chosen the latter approach, since the eigenvalues of $\hat{S}_{ij}$ give us significant information about the nature of the retrieval problem. Consider, for the moment, the case where all the σ_j^2 are equal and uncorrelated.

In this case, D_{jj} is a scalar multiple of the identity matrix;

$$\hat{S}_{ij} = S_{ij} + \sigma^2 \delta_{ij}.$$

The eigenvectors of $\hat{S}_{ij}$ are the same as the eigenvectors of S_{ij} , and the eigenvalues λ_k of S_{ij} are related to the eigenvalues $\hat{\lambda}_k$ of $\hat{S}_{ij}$ by $\hat{\lambda}_k = \lambda_k + \sigma^2$.

Let $\underline{e}_k$ be the k^{th} eigenvector of $\hat{S}_{ij}$ (or S_{ij}); we wish to represent (for the moment)

$$p_i = \sum_j \alpha'_{ij} \beta_j$$

where $\beta_j = \sum_n e_{jm} T_m$

Then $\alpha'_{ik} = \sum_j \frac{1}{\lambda_k} \sigma_{ij} e_{jk}$

and it is clear that if $|\lambda_k|$ is very small α'_{ik} will be very large and the contribution to

$$\sigma_{Ni}^2 = \sigma^2 \sum_j \alpha_{ij}^2$$

will be correspondingly very large.

We must, therefore, keep in mind the values of σ_j^2 when we design the retrieval, for two reasons. One is that, when $\sigma_j^2 = 0$, we would have

$$\alpha'_{ik} = \sum_j \frac{1}{\lambda_k} \sigma_{ij} e_{jk}$$

and the expansion coefficients would tend to infinity for small values of λ_k . The other reason is that eigenvectors with values of $\lambda_k < \sigma^2$ contribute very little information to the retrieval. We wish to retrieve the values of four parameters; we can do this, roughly speaking, only if at least four of the λ_k are greater than σ^2 .

We should, at this point, bring up the question of the validity of a linear retrieval method, since the brightness temperatures are not linear in the parameters. We shall reserve judgment on the utility of non-linear methods until we have discussed the following point.

The field of view of the SMMR instrument, at the longest wavelength, is 156 km on a side. We can be certain, a priori, that the meteorological parameters will not be constant within the field of view. We wish to retrieve average values of the parameters, and want these values to be unbiased. In this context, unbiased means that the average of a large number of values of some parameter p retrieved from the observations will not be systematically different from the true average value of that parameter.

Let us break up the field of view into N regions of equal area, with the conditions uniform in each region. We take, as an example, the case where we retrieve the parameters as

$$p_i = \sum_j \left(\alpha_{ij} T_j + \beta_{ij} T_j^2 \right).$$

where T_j is the average value of the j^{th} brightness temperature over the field of view. Let T_{kj} be the brightness temperature in the j^{th} channel in the k^{th} region, and p_{ki} the value of the i^{th} parameter in that region. The value we wish to retrieve is

$$\langle p_i \rangle = \frac{1}{N} \sum_k p_{ki}.$$

However, the value we will retrieve is

$$p_i = \frac{1}{N} \sum_j \left(\alpha_{ij} \sum_k T_{kj} + \frac{1}{N} \beta_{ij} \left(\sum_k T_{kj} \right)^2 \right)$$

The difference between $\langle p_i \rangle$ and p_i , which is a bias in our retrieval, is

$$p_i - \langle p_i \rangle = \frac{1}{N} \sum_j \beta_{ij} \left[\left(\sum_k T_{kj} \right)^2 - \sum_k T_{kj}^2 \right] ;$$

we note that the term in square brackets is the variance of T_j over the field of view. Thus, we can write

$$p_i - \langle p_i \rangle = - \sum_j \beta_{ij} \text{var} \left(T_j \right) .$$

We see that by including quadratic terms in the retrieval, we may increase the accuracy of the retrieval for the case where the conditions are homogeneous within the field of view at the expense of biasing the result when the conditions are not homogeneous. This point will be treated again in Section 5.

SECTION 4 - ACCURACY OF THE RETRIEVALS

In the section, we shall consider the (somewhat unrealistic) case where the meteorological parameters are constant within a field of view of the SMMR instrument, which we call the "homogeneous" case. The problem introduced when the rain rate is allowed to vary within the field of view (FOV) ("non-homogeneous" case) will be treated in the next section. The primary purpose for presenting the results in this section is not one of developing a retrieval algorithm -- for this, we must consider the non-homogeneous case -- but to provide a comparison of the non-homogeneous case, and underscore the importance of considering the case where the rain rate varies over the FOV.

We have written a program that used the ensemble of calculated brightness temperatures to calculate expansion coefficients for retrieving freezing level, rain rate, wind speed, sea temperature, and the optical depth at $.22 \text{ cm}^{-1}$. The program then calculates the standard deviation of the retrieval, including the effect of the noise in the radiometer. In Table 1 we present some representative results for the homogeneous case, where we have made a linear, quadratic, or logarithmic fit to the ensemble of models. Columns 1 and 2 show the range of τ over which the subset of the entire ensemble was selected. Column 3 shows which type of retrieval was used. Column 4 shows the restriction on the wind speed in the models selected, if any. The next five columns give the standard deviations in freezing level (h), rain rate (r), wind speed (w), sea surface temperature (T_s), and rain opacity (τ). For the quadratic retrievals, the biases discussed in Section 3 are also given.

We see that, as we would expect, the error in the retrieval increases as τ (and hence the rain rate) increases. We can also see that the quadratic retrieval is more accurate than the linear retrieval because it fits the relationship between the brightness temperatures and meteorological parameters better. The logarithmic retrieval is no better than the quadratic retrieval, is harder to analyze for bias, and will not be considered further.

In Table 1 we show the bias in a quadratic retrieval, as we discussed in the last section. While we cannot know what the variance in T_B will be over the field of view, for computational purposes we have used the variance of each T_B in the subset of the ensemble that was used to calculate the retrieval coefficients. The biases calculated in this manner are not small compared with the standard deviation of the retrieval; this supports the notion that we should not use quadratic terms in the final evaluation of the parameters, but rather use a linear fit over a suitably restricted range of τ . Which range to use might be decided by using a quadratic fit over the entire range of τ to find a provisional value of τ .

We also note from Table 1 that for some of the retrievals, the subset of models used to calculate retrieval coefficients was restricted to wind speed greater than 7 m s^{-1} or to wind speeds less than 7 m s^{-1} (the relationship between speed and ocean reflectivity has a discontinuity in its slope at 7 m s^{-1}). We see that, by using coefficients taken from the appropriate subset of models, and having an approximate value for wind speed, we can make a modest improvement in the retrieved value of the wind speed, and a considerable improvement in the value of the ocean temperature.

The emissivity of sea water changes due to changes in both wind speed and sea surface temperature. Having some a priori knowledge of wind speed helps to reduce the uncertainty in the sea temperature.

We now turn to a different problem. Because only one antenna is used for all five frequencies, the field of view is different at different frequencies. Thus, at the lowest frequency, the effective integration time is longer than for higher frequencies, and therefore, the receiver noise will be smaller. This fact somewhat complicates the analysis of the retrieval problem. First, let us look at the effects of deleting some channels from the retrieval, but leaving the receiver noise the same for all channels (here $\sigma^2 = 0.04$ K). In Table 2 we show how the standard deviation in each parameter changes as we delete different channels. We see that, with only a small increase in the error, the wind speed and ocean temperature can be found from the 6.6- and 10- GHz channels alone. This corresponds to finding the average values over the largest field of view for these parameters; using the higher-frequency channels will not give significant information about the wind speed and sea temperature on a smaller spatial scale.

For the data analysis, four cell sizes have been adopted that correspond roughly to the field of view at different frequencies. The cell sizes are 156 km at 6.6 GHz, 97.5 km at 10 GHz, 60 km at 18 and 21 GHz, and 30 km at 37 GHz. We can retrieve the wind speed and ocean temperature only on the 156 km scale.

We have a choice of how to proceed with the freezing level and rain rate. These parameters can be retrieved from the 18-, 21-, and 37- GHz data alone, on a 60-km scale. It probably

would not help the retrieval much to include the 6.6- and 10-GHz data from the appropriate 160-km cell, as, while the retrieval is somewhat improved by adding the low-frequency channels, the average value over the 160-km cell may not be representative of the conditions in a particular 60-km cell. Similarly, we could try to calculate rain rate and freezing level on a 30-km scale, but this would require using average values on a 60-km cell for the 18- and 21-GHz channels. It is not clear without further study and some experience with real data what the retrievals on the 30-km scale would mean, although analysis of the 37 GHz data on this scale certainly will give information on how uniform conditions are on the larger scale.

In Table 3 we show how the standard deviation in the retrieval changes as we use different cell sizes. The values of σ^2 used are given on the left, and the standard deviations of the retrieval of the parameters are given on the right. The reason that the noise changes with cell size is that the integration time is longer if, for example, we average the 37 GHz data over four 30-km cells than it is for one 30-km cell. The noise figures adopted here are believed to be representative of the SMMR instrument (which has not been launched at the time of this writing). In each group, there are four cases presented, that correspond to retrievals on the 156-, 90-, 60-, and 30-km cell sizes. For the 90- and 60-km cells, we delete the 6.6-GHz, and the 6.6- and 10- GHz channels respectively. The fourth retrieval, on the 30-km scale, uses the 37- GHz channel for the 30 km cell, and the 18- and 21- GHz channels from the corresponding 60- km cell.

In our calculations, we have calculated the values of χ_i^2 and σ_{Ni}^2 separately for each parameter. In the case of a linear retrieval over some range in τ , χ_i^2 is reduced by reducing the

the size of the interval, while σ_{Ni}^2 is not appreciably affected by the size of the interval. In an attempt to develop an optimal retrieval algorithm, it would seem that we should divide the range of τ into intervals small enough so that $\chi_i^2 \approx \sigma_{Ni}^2$, and then compute a different set of linear retrieval coefficients for each interval of τ . Then, for each observed set of ten values of T_B , we would decide which interval the value of τ is in and use the appropriate set of retrieval coefficients. In this sense, the size of the interval will depend on the values of σ_i^2 .

However, as we shall see in the next section, there are other considerations that will preclude making the intervals in τ small enough so that $\chi_i^2 \approx \sigma_i^2$. It seems, for our analysis of the retrieval problem, that χ_i^2 will be larger than σ_i^2 , and as long as the noise values that obtain in the spacecraft are not too much larger than the ones we have used, the results will not be significantly dependent on these values. The largest errors, by far, in the retrieval are due to the non-linear nature of the dependence of the brightness temperatures on the meteorological parameters and to the uncertainties of calibrating the spacecraft observations with suitable ground truth.

Standard Deviation		Bias										No. of Samples		
T	T	L, Q or ϵ_n	w	h	r	w	T _S	T	h	r	w	T _S	T	
min	max		m/s	km	mm/hr	m/s	K	$\times 10^4$	km	mm/hr	m/s	K	$\times 10^4$	
0	0	Q		.23	3.2	2.4	1.6	68.	1.3	1.8	-12.	-8.0	370	1880
0	0	Q	<7	.18	2.8	1.6	1.5	46.	2.4	-9.3	-12.	-13.0	200	900
0	0	L		.42	4.6	3.7	2.8	140.						1880
0	0	ϵ_n		.42	4.4	4.0	3.1	160.						1880
0	.011	Q		.075	.18	.43	.92	1.8	.20	-.41	.17	.11	-.74	674
0	.011	L		.11	.25	.46	1.2	3.4						674
0	.011	L	<7	.10	.22	.36	.38	2.5						285
0	.011	L	>7	.11	.23	.26	.42	3.1						389
0	.025	Q		.11	.35	.47	.99	2.7	.29	-.64	.15	.14	1.0	897
0	.025	L		.17	.47	.49	1.2	4.5						897
0	.025	L	<7	.16	.42	.37	.42	3.1						381
0	.025	L	>7	.16	.44	.29	.45	4.1						561
0	.025	ϵ_n		.21	.39	.50	1.2	3.6						897
0	.25	Q		.23	3.0	1.9	1.4	51.	1.1	2.7	-6.7	-3.9	220	1665
.01	.05	Q		.11	.60	.52	1.0	4.3	.27	-.65	-.20	-.64	1.1	444
.01	.05	L		.18	.76	.55	1.2	5.9						444
.01	.05	L	<7	.17	.70	.46	.52	4.4						191
.01	.05	L	>7	.17	.75	.35	.52	5.8						253
.01	.05	ϵ_n		.27	.77	.58	1.2	7.6						444

TABLE 1.

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Standard Deviation										Bias			No. of Samples	
T	T	L, Q or En	w	h	r	w	T _s	r	h	r	w	T _s	r	
min	max		m/s	km	mm/hr	m/s	K × 10 ⁴	mm/hr	km	mm/hr	m/s	K × 10 ⁴		
.025	.075	Q		.070	.79	.59	1.1	6.3	.15	.017	-.25	-.63	5.3	307
.025	.075	L		.12	.89	.66	1.2	8.7						307
.025	.075	L	>7	.12	.90	.46	.62	7.2						175
.025	.075	L	<7	.12	.85	.60	.69	7.2						132
.025	.075	En		.20	1.4	.82	1.3	16.						307
.1	.2	Q		.080	1.9	1.5	1.3	40.	.089	-.63	-.11	-.46	10.	265
.1	.1	L		.12	2.2	1.6	1.4	44.						265
.1	.2	L	<7	.12	2.0	1.5	1.4	32.						112
.1	.2	L	>7	.12	2.2	1.5	1.1	45.						153
.1	.2	En		.15	2.4	1.9	1.6	51.						265
.2	.3	Q		.090	1.5	1.6	1.2	33.	.045	-.079	-.46	-.39	14.	176
.2	.3	L		.11	1.6	1.9	1.4	41.						176
.2	.3	L	<7	.10	1.6	1.7	1.4	30.						75
.2	.3	L	>7	.11	1.6	1.6	1.2	41.						101
.2	.3	En		.11	2.1	2.1	1.5	44.						176
.3	.4	Q		.070	.70	2.5	1.5	53.	.013	-.048	-.10	-.14	7.6	113
.3	.4	L		.080	.79	2.9	1.7	62.						113
.3	.4	L	<7	.061	.79	2.0	1.6	35.						48
.3	.4	L	>7	.080	.79	2.5	1.5	62.						65
.3	.4	En		.086	.91	3.5	2.0	79.						113

TABLE 1 (cont)

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Channels Used (Ghz)					Standard Deviation					No. of Samples
6.6	10	18	21	37	h km	r mm/hr	w m/s	T _s K	τ x 10 ⁴	
0 < τ < .011										
X	X	X	X	X	.11	.25	.46	1.2	3.4	674
	X	X	X	X	.12	.25	.71	1.6	5.2	
X		X	X	X	.12	.25	.52	1.2	4.6	
		X	X	X	.13	.26	2.3	3.2	6.6	
		X	X	X	.14	.28	3.9	3.7	8.6	
X	X	X			.21	.35	.46	1.2	4.3	
X	X				.69	.51	.47	1.2	8.7	
.01 < τ < .05										
X	X	X	X	X	.14	.76	.55	1.2	5.9	444
	X	X	X	X	.18	.75	1.2	1.6	11.	
X		X	X	X	.18	.77	.67	1.2	10.	
		X	X	X	.23	.83	3.4	2.9	11.	
		X	X	X	.25	.92	5.2	3.4	15.	
X	X	X			.31	1.0	.60	1.2	8.2	
X	X				.71	1.5	.64	1.2	16.	
.05 < τ < .1										
X	X	X	X	X	.095	.82	.72	1.2	12.	195
	X	X	X	X	.12	.85	2.5	2.0	25.	
X		X	X	X	.10	.84	1.1	1.4	25.	
		X	X	X	.13	.85	5.6	2.9	27.	
		X	X	X	.15	.86	6.9	3.5	28.	
X	X	X			.15	1.1	.74	1.3	14.	
X	X				.55	2.7	1.2	1.3	35.	

TABLE 2

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Channel (GHz)				Standard deviation					No. of Samples
6.6	10	18	21	37	h km	r mm/hr	w h/s	T _s K	τ x 10 ⁴
0 < τ < .011									
.040	.040	.040	.040	.040	.11	.25	.46	1.2	3.4
	.040	.048	.058	.040	.12	.26	.71	1.6	5.2
		.20	.23	.073	.13	.29	2.7	3.2	7.2
		.20	.23	.29	.14	.31	2.8	3.3	7.6
.01 < τ < .05									
.040	.040	.040	.040	.040	.18	.76	.55	1.2	5.9
	.040	.048	.058	.040	.18	.77	1.2	1.6	11.
		.20	.23	.073	.25	.90	4.1	3.0	13.
		.20	.23	.29	.28	1.0	4.6	3.2	15.
.05 < τ < .1									
.040	.040	.040	.040	.040	.095	.82	.72	1.2	12.
	.040	.048	.058	.040	.12	.85	2.6	2.0	25.
		.20	.23	.073	.14	.89	6.4	3.5	28.
		.20	.23	.29	.15	1.0	6.5	3.5	32.

TABLE 3

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SECTION 5 - PROBLEMS WHEN THE FIELD OF VIEW
IS NON-HOMOGENEOUS

So far, everything we have said concerns only the case where the meteorological conditions are homogeneous within the field of view (FOV). We must be prepared, however, to deal with the situation -- which probably will occur more frequently than not -- where only some fraction f of the FOV is covered by rain. To investigate this problem, we constructed a set of what we call "non-homogeneous" models. We use the homogeneous ensemble to generate the non-homogeneous set by, for a given sea temperature, cloud height, and wind speed, constructing a set with

$$T'_{Bi} = f T_{Bi}(r) + (1 - f) T_{Bi}(0)$$

$$r' = fr$$

$$\tau' = f\tau$$

where $T_{Bi}(r)$ is the brightness temperature in the i^{th} channel at the rain rate r , τ is the raindrop opacity at $.22 \text{ cm}^{-1}$, and $0 \leq f \leq 1$.

We can calculate the retrieval coefficients from either the homogeneous or non-homogeneous ensemble of models. For the latter case, we also calculate the coefficients to retrieve the fractional area covered by rain, f . (In this case, we do not calculate coefficients to retrieve the cloud height.) We call these sets of coefficients, again, "homogeneous" or "non-homogeneous". We have used both sets of coefficients to retrieve the parameters of both ensembles of models over several ranges of τ . Some results are shown in Table 4. The first two columns show which coefficients and which ensemble was used (H = homogeneous, N = non-homogeneous). The subset used for the particular

retrieval was based on the value of τ ; the smallest and largest rain rates and the number of models are given in the last three columns. Tables 5 and 6 compare retrievals based on all 10 channels, and only the 6 highest-frequency channels, respectively. The show the standard deviation in the retrievals; f is the fraction of the FOV covered with rain, and its retrieval is only valid when both the ensemble and coefficients are non-homogeneous. We see, as we did in Table 2, that omitting the 6- and 10- GHz channels has only a small effect on the retrieval of f and the rain rate r .

The first point to note is that we can, with some confidence, retrieve the value of f if we have used the non-homogeneous coefficients with the non-homogeneous ensemble of models. The standard deviation of the retrieval of f is about .02 - .08, while $0 \leq f \leq 1$.

The second -- and more important -- point is that we cannot use the homogeneous coefficients with the non-homogeneous ensemble of models. For example, if we use the H coefficients with the N ensemble of models, in the range $.01 < \tau < .05$ ($2.25 < r < 15$) we find that standard deviation for rain rate is 9.1 mm hr^{-1} for the linear retrieval, which is a useless result.

It is also clear that retrievals using quadratic terms fare very poorly; the reason is that the importance of the difference between $(T_1 + T_2)^2$ and $T_1^2 + T_2^2$ is magnified in the non-homogeneous case (see the discussion of the bias on §III).

This illustrates one difficulty of relying on models to interpret the data from the SMMR instrument -- or any other sounding instrument. We have just seen a retrieval scheme, as we outlined in Section 3, that looked good with computer simulations, which would in fact have been very bad. We also must note, here, that the problems will increase even further if, i) there are more than two rates of rain in the field of view, and; ii) the other parameters vary also.

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Standard Deviation

coeffi- cients	ensemble	f	r			τ mm/hr	τ mm/hr	τ mm/hr	τ mm/hr	No. of Samples
			mm/hr	m/s	τ mm/hr					
0.0 < τ < 0.011										
H	H	--	.25	.46	1.1	3.4	0	3.75	674	
N	N	.084	.28	.52	1.0	12.	0	3.75	3764	
H	N	--	.48	.66	1.2	17.	0	3.75	3764	
0.01 < τ < 0.02										
H	H	--	.26	.47	1.2	3.5	2.	7.5	196	
N	N	.023	.56	.80	1.2	25.	1.1	7.5	571	
H	N	--	21.	1.4	6.2	69.	1.1	7.5	571	
0.01 < τ < 0.05										
H	H	--	.76	.56	1.2	5.9	2.	15.	444	
N	N	.025	1.3	1.7	1.7	63.	1.1	15.	1204	
H	N	--	11.	2.7	2.3	81.	1.1	15.	1204	
0.01 < τ < .05 (quadratic)										
H	H	--	.60	.52	1.0	4.3	2.	15.	444	
N	N	.020	1.2	1.5	1.5	57.	1.1	15.	1204	
H	N	--	15.	3.2	3.6	110.	1.1	15.	1204	
0.02 < τ < 0.025										
H	H	--	.016	.48	1.1	1.9	3.75	6.25	66	
N	N	.019	.51	.63	1.1	14.	2.45	8.75	175	
H	N	--	7.4	8.0	4.5	49.	2.45	8.75	175	
.015 < τ < .030										
H	H	--	.44	.50	1.1	4.0	3.75	10.	210	
N	N	.021	.83	1.1	1.3	38.	2.0	10.	567	
H	N	--	32.	6.2	6.9	49.	2.0	10.	567	

TABLE 4

Standard Deviation

coeffi- cients	ensemble	f	mm/hr	m/s	T _s K	τ $\times 10^4$	τ min mm/hr	τ max mm/hr	No. of Samples
			0.050 < τ < 0.10						
H	H	--	.77	.71	1.2	12.	10.	25.	195
N	N	.021	2.1	2.2	1.9	83.	5.5	25.	370
H	N	--	55.	7.2	20.	270.	5.5	25.	370
			0.10 < τ < 0.15						
H	H	--	1.4	.96	1.2	21.	15.	40.	178
N	N	.018	2.8	2.5	2.0	89.	12.	40.	152
H	N	--	50.	7.0	15.	220.	12.	40.	152
			0.10 < τ < 0.10						
H	H	--	2.1	1.6	1.4	44.	15.	40.	265
N	N	.018	3.3	3.1	2.3	100.	12.	50.	235
H	N	--	28.	12.	8.3	510.	12.	50.	235
			0.050 < τ < 0.075						
H	H	--	.57	.60	1.2	4.9	10.	20.	125
N	N	.019	1.6	1.6	1.5	57.	5.5	21.	242
H	N	--	53.	2.7	30.	190.	5.5	21.	242
			0.03 < τ < .05						
H	H	--	.44	.55	1.1	4.0	6.25	15.	119
N	N	.020	1.2	1.3	1.4	44.	3.5	15.	316
H	N	--	58.	3.4	19.	220.	3.5	15.	316

TABLE 5

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Standard deviation

TABLE 6

SECTION 6 - COMMENTS

A few words should be said about the problem of verification of the SMMR retrieval. In view of what has been said above, it is clear that the SMMR data will be worthless without verification of the retrieval values of the meteorological parameters by comparison with ground-based observations. For the moment, let us consider only the rain rate problem.

Common experience tells us a few things about the nature of the rainfall distribution. One is that the spatial rainfall pattern is more or less constant over a time scale of about one hour. The second is that, as we view it from one point on the ground, the rainfall rate usually changes very rapidly on this time scale. This rapid change is due, in large part, to the motion of the rainfall pattern over the ground. Thus, the common experience is that, on a scale of 30 - 150 km, the rainfall rate will not be uniform most of the time. This qualitative argument alone suffices to indicate that we must consider the retrieval problem in the case where only some fraction f of the field of view is covered by rain clouds.

One type of observation potentially available to us is data from the aircraft SMMR simulator. Since the aircraft altitude is very small compared to that of the satellite, the field of view is corresponding smaller. Hence, experiments done with the aircraft underflying the satellite, and sampling rapidly many points in the satellite field of view, would give us information as to the distribution of brightness temperature in the satellite field of view.

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The problem, of course, is that the speed of the sub-satellite point for NIMBUS G will be about 2300 km hr^{-1} , which is somewhat faster than any aircraft can fly. Even getting a minimal sample of aircraft data would require, probably, more flight time than is feasible. While it is probably not feasible to use aircraft data to calibrate the SMMR data, such observations would be invaluable to test the validity of the models, if they were made in a manner that allowed us to get simultaneous rainfall rate data. If the problem of getting enough aircraft data to compare with the SMMR satellite data is severe (primarily, of course, this is due to financial considerations), the problem of getting rain rate data on the ground (or rather the sea surface) from rains gages is worse. There is no network of rainfall gages on the ocean, partly for economic reasons, and partly because it is difficult to make the measurement with existing types of equipment while at sea. The only available data would have to come from the few radar weather stations that are close enough to the shore to provide adequate coverage over the ocean, e.g., the one in Miami, Florida. It might also be possible to use ship-borne radar, if such a facility could be made available.

APPENDIX A - ATMOSPHERE OPACITY

In Table A-I, we show the amount of water vapor and the no-rain optional depth at each frequency for the models used in this study.

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TABLE A-1

ATMOSPHERIC OPACITY TABLE FOR A LAPSE RATE OF 6.5 deg/km

Freezing Level (km)	Water Vapor (cm)	a t m o s p h e r i c o p a c i t y				
		.22 cm ⁻¹	.356 cm ⁻¹	.6 cm ⁻¹	.7 cm ⁻¹	1.23 cm ⁻¹
5	7.056	1.3679 x 10 ⁻²	2.8707 x 10 ⁻²	.1365	.3686	.2090
4	4.534	1.2235 x 10 ⁻²	2.3682 x 10 ⁻²	9.8791 x 10 ⁻²	.2504	.1744
3	2.715	1.13 x 10 ⁻²	2.0196 x 10 ⁻²	7.2203 x 10 ⁻²	.1666	.1495
2	1.567	1.0736 x 10 ⁻²	1.782 x 10 ⁻²	5.36 x 10 ⁻²	.1088	.1318

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